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How the ability to analyse tendencies influences decision satisfaction

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Abstract. Using agents to represent decision-makers is a complex task. It is important that agents can understand the context and be more proactive. Here we propose a model and an algorithm that will allow the agent to analyse tendencies regarding the number of supporters for each alternative along the process. It is intended that agents can be more dynamic and intelligent and can evaluate different contexts throughout the decision-making process. We believe agents will achieve better and consensual decisions more easily. We tested our model in three simulation environments with different complexity levels. Our model proved that agents that use it will obtain higher average consensus and satisfaction levels. Besides that, agents using this model will obtain those higher consensus and satisfaction levels in most of the times compared to agents that do not use it.

Keywords: Group Decision Support Systems, Argumentation, Decision Satisfaction, Automatic Negotiation, Multi-Agent Systems.

1 Introduction

The future and success of organizations depend greatly on the quality of every decision made. It is known that most of the decisions in organizations are made in group [23]. To support this type of decision, the Group Decision Support Systems (GDSS) have been widely studied throughout last decades [7, 8, 14]. However, over the last ten/twenty years, we have seen a remarkable change in the decision-making context, especially in large organizations [11, 25]. With the appearance of global markets, the growth of multinational enterprises and a global vision of the planet, we easily find chief executive officers and top managers (decision-makers) spread around the world, in countries with different time zones. To provide an answer and operate correctly in this type of scenarios the traditional GDSS have evolved to what we identify today as Ubiquitous Group Decision Support Systems (UbiGDSS). The UbiGDSS support the decision-making process by using the main characteristics of ubiquity ("anytime" and "anywhere") [5, 22].

There are some works in the literature that address the term of UbiGDSS [22]. The UbiGDSS may present different complexity levels. They can provide information about decision-maker preferences and other simple statistical information [32, 16]. They can also follow the entire decision-making process using agents that represent decision-makers. These agents will use automatic negotiation models to solve problems finding consensual alternatives that provide a satisfaction level [28, 3, 1]. However, most

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of published works address the decision in a completely different perspective. In literature, we find many proposed works that deal with the topic of decision-making using agents, argumentation models, heuristics, etc. [27, 24, 10, 18]. However, the type of the decision and how it is oriented in those works is completely different from the decision-making context where organizations make use of UbiGDSS. For instance, in most of works in the literature that use agents to perform automatic negotiation tasks, they will be either fully competitive or fully collaborative. This claim can be proved by considering the seller-buyer strategy which is one of the most known and used examples in literature [29, 19, 20, 9]. To support decision-making groups that represent an entire organization while using automatic negotiation mechanisms, it is necessary to pay close attention to some details. First, we cannot forget that the system will be used by humans and therefore must provide information that they understand. Second, it is necessary to involve the decision-maker in the decision-making process, so that he can understand suggestions given to him and be confident enough to accept them. It is very important that the decision-maker understands the logic behind such suggestions. Finally, it is essential to find solutions which result from the exchange of knowledge and the creation of intelligence [6, 13]. In this type of context, it is not the right approach to take advantage of the agent's lack of knowledge just to place him in a better position to accept a certain request. We are considering a context where there will be a combination of both competition and collaboration.

In this work, we study how the decision-making group can obtain higher consensus and satisfaction levels by giving agents the ability to predict the final satisfaction level, which theoretically should lead to decisions with more quality. For that, we propose a model and an algorithm that will allow agents to identify an alternative tendency and that will result in the agent redefining objectives and obtaining a higher satisfaction level compared to the case where he does not make that redefinition. The model is structured in two parts. In the first part, whenever the agent identifies an alternative tendency, he will verify if new alternatives should be added to his objectives. In the second part, the agent will analyse and select the best alternative from his objectives to make a request at a certain time.

The hypotheses which we intend to analyse in this work are: (h1) intelligent agents are capable to understand the context and show flexibility to make better decisions, (h2) agents able to predict the final satisfaction level make decisions easier (achieve a higher consensus level) and (h3) agents able to predict the final satisfaction level make more satisfactory decisions (the perception of the agent's quality level is higher). To test the proposed model and algorithm we have used an argumentation model adapted to the context of this work and that has been introduced before. Several experiments were performed in three simulation environments with different complexity levels. The goal was to compare agents with the ability to analyse tendencies with agents without the same ability. We have anticipated that agents able to analyse tendencies and redefine objectives, and therefore being more flexible, will be able to achieve decisions with more quality and with higher consensus levels.

The rest of the paper is organized as follows: in the next section our approach is presented, where the model and the algorithm are described. In the section 3 we present the evaluation done to our work and report the obtained results. Finally, some conclusions are taken in section 4, along with the work to be done hereafter.

2 Methods

Being able to predict the final satisfaction level may have a great impact on the final satisfaction level of the decision-maker, on the decision group and on the decision quality. We can only make such statement due to the relation existing between the satisfaction and the perception of the decision quality [12]. It is considered that the final satisfaction of a decision-maker or a group of decision-makers reflects the perception of quality and other things [3, 4, 5]. To measure satisfaction some aspects can be considered such as: the results, the process, the defined behaviour or the strategy towards a certain problem, the interactions, etc [3]. In order to predict satisfaction (in a human way) it is first necessary to have the sensitivity to do so and secondly it is necessary to have the knowledge about the context (which sometimes may not be possible).

As introduced in literature the satisfaction can be used as a metric (effective and efficient) to validate the quality of negotiation models, group decision support systems, etc [3]. It is important to note that the satisfaction is widely used in literature as a metric for many other things, such as: life satisfaction

[31], job satisfaction [17], etc.

In many existing negotiation models, agents will send requests hoping that other agents will accept them. They use arguments that can justify requests and persuade other agents [30, 15]. Besides that, it is very common to see agents that use algorithms to identify moments when they can accept a certain request [21]. In this work, we study a new concept, which is the agent's ability to analyse tendencies, and how that will affect the final satisfaction and the ability to reach consensus. We will consider that a decision-maker, within a scale [0..1] will do the following alternatives' appreciation: $\{[Alt1, 0.89], [Alt2, 0.54], [Alt3, 0.34], [Alt4, 0.11]\}$. To simplify our scenario, we assume that the final satisfaction level is equivalent to the appreciation done to the chosen alternative, which corresponds to the alternative with the highest consensus level after 10 rounds or the first alternative to reach a consensus greater than 75% of all the participants. Let us suppose that an agent has an acceptance range of 0.20, which would allow him to accept all the alternatives (according to his preferred alternative) that vary between 0.89 and 0.69. Therefore, the agent would never be in conditions to accept any requests. This also means that even in case that only one more acceptance is needed for $Alt2$ and $Alt4$ to reach the 75%, the same agent would still seek $Alt1$ as his only objective for that meeting. This way the agent would be losing a clear opportunity to reach a final satisfaction level of 0.54, and instead would only reach a satisfaction level of 0.11. Besides this, even if the acceptance range would allow the agent to accept $Alt2$, if that alternative was never requested to him, he would never consider it as an objective. Given that agents must demonstrate a social behaviour equivalent to human beings, and that they should demonstrate and generate intelligence, this does not seem to be the best approach.

The goal of this work is to prevent these situations from happening. Therefore, the main idea is to provide an agent with the ability to identify tendencies and to be able to redefine his objectives. This is why we believe that it is possible to maximize the satisfaction of every agent as well as the entire group, which will result in decisions with much higher quality.

Our model is very simple and is based in the Algorithm 1 (written in pseudocode):

```
Let Ag1 be the agent;
Let AltsNP be the list of all alternatives still not preferred by the Ag1;
Let altTendency be the alternative of the tendency;
Let AltsObj be the list of all alternatives which can be considered as an objective to Ag1;
Let altPref be the preferred alternative to Ag1;
Let newAlt be the new alternative to be added to AltsObj;
begin
    resultNewAlt ← 0;
    resultTendency ← Result(altTendency);
    resultPref ← Result(altPref);
    if (resultTendency > resultPref) then
        foreach alt ∈ AltsNP do
            resultAlt ← Result(alt);
            if (
            (preference (alt) > preference (altTendency)) and
            (resultAlt > resultTendency) and
            (resultAlt > resultNewAlt)
            ) then
                resultNewAlt ← resultAlt;
                newAlt ← alt;
            end if
        end foreach
        if (resultNew! = 0) then
            AltsObj.add(newAlt);
        end if
end
```

Algorithm 1: Tendency identification algorithm

The model is based mainly on two parts. In the first part, a tendency is identified and the agent will verify if there are any conditions that allow him to add another alternative (different from his initial preferred alternatives) to his list of objectives. Every time an agent saves the knowledge about a new alternative preference for another agent he will use the formula 1 in order to measure the tendency result for that new alternative (in pseudocode it is equivalent to the Result() tag). In case he verifies that tendency already has a higher result compared to his preferred alternative (once again using formula 1), he will analyse all the alternatives that are still not part of the list of his objectives and verify if there is any alternative with a preference greater than the tendency. From the list of all possible alternatives that fit this condition he will select the one which provides the highest result and add it to his list of objectives. The agent will then be able to choose that alternative for future requests.

The second part is related with how the agent chooses, from his list of objectives, which alternative should be used for a request. For that, he will use the formula that measures the "result" and only considers alternatives from his list of objectives. It is assumed that the initial preferred alternatives by the agent are also included in his list of objectives. The formula 1 is used to measure the result for each alternative in the list of objectives. This formula is very simple and considers the alternative evaluation done by the decision-maker, the percentage of participants in favour of that alternative at a certain time during the discussion and two dimensions related to the behaviour style of the agent (according to the work proposed in [26]). Since the evaluation is private information the formula relates that evaluation with the dimension of Concern for Self, and since the number of participants in favour of the alternative is public information the formula relates that information with the dimension of Concern for Others. This allows agents to act according the behaviour style defined by the representing decision-maker. It is also possible to identify and avoid certain situations, such as an agent defined with a Dominating behaviour to easily follow a tendency when the decision-maker expects him to have a stricter and less collaborative attitude.

$$A_{Result_{Alt_x}} = \frac{Alt_x \times CS + \left(\frac{NS}{ND}\right) \times CO}{CS + CO} \tag{1}$$

Where:

- Alt_x is the assessment done to the alternative for which the result is being measured;
- CS is the value of Concern for Self $[1, 2, 3]$;
- NS is the current number of agents supporting Alt_x;
- ND is the total number of participating agents;
- CO is the value of Concern for Others $[1, 2, 3]$.

In case an agent without a defined behaviour is being considered, the formula can also be used by giving the same value to CS and CO variables (for example "1") for that agent. The alternative that provides the highest A_{Result} will be chosen whenever the agent makes a new request. This formula will allow the agent to define his objectives according to the importance of the alternatives and how likely they are to be chosen at a certain time during the discussion.

3 Evaluation and Results

The considered scenario involves agents' negotiation to solve the problem of choosing a desktop monitor for an organization that wants to purchase 200 new desktop monitors to one of its subsidiaries. Each agent intends to represent one member of the organization administration board. Each alternative has been classified according to five criteria: Size (numerical, without value), Resolution (numerical, maximization), Hz (numerical, maximization), Ms (numerical, minimization) and Price (numerical, minimization).

In Table 1, all specifications are presented for each considered alternative. The satisfaction and the consensus level are used as metrics to evaluate the overall performance in different scenarios. The satisfaction metric is used to understand the quality perception (of the decision-maker that is represented) towards the chosen alternative or the alternative supported by most agents at a certain time. For that,

Table 1: Multi-Criteria Problem

Alternatives	**Size**	**Resolution**	**Hz**	**Ms**	**Price**
Asus 27” ROG SWIFT PG278Q	27	2560*1440	144	1	699,99€
BenQ 27” XL2720Z	27	1920*1080	144	1	489,00€
AOC 24” E2476VWM6	24	1920*1080	60	1	154,90€
BenQ 2” XL2430T	24	1920*1080	144	1	399,00€
LG 27” 27MP37VQ-B	27	1920*1080	60	5	210,80€
Asus LED 21.5k” VS228HR	21,5	1920*1080	60	5	129,90€
Samsung LED 22” S22C570H	22	1920*1080	60	5	179,90€
BenQ 24” LED BL2420PT	24	2560*1440	60	5	399,90€
Asus LED 24” VG248QE 144Hz 3D	24	1920*1080	144	1	288,90€
Samsung 24” Curvo LED S24E500C	24	1920*1080	60	4	199,90€

the notion of satisfaction that is used is the one proposed in [12]. The satisfaction is measured in two parts (for agents without a defined behaviour only the first part is considered). It is first measured objectively through the formulas 2, 3 and 4.

$$D_{Lost} = Alt_F - Alt_P \tag{2}$$

$$D_{Lost} = 2Alt_F - 1 \tag{3}$$

$$D_{Satisfaction} = (1 - |A_{Conversion}|) \times D_{Lost} + A_{Conversion} \tag{4}$$

Where:

- D_{Lost} is the loss of decision maker’s satisfaction based in the difference between assessments made for the alternative chose by the group and for his preferred alternative. The loss is zero when the chosen alternative is the same as his preferred alternative;
- Alt_F is the assessment made by the participant for the final alternative, alternative chosen by the group;
- Alt_P is the assessment made by the participant for his preferred alternative;
- $A_{Conversion}$ is the conversion of the assessment made by the participant in the range $[-1..1]$.

The second part relates the $D_{Satisfaction}$ and the behaviour defined by the decision-maker. In this second part, the satisfaction is measured according to the values of the agent’s defined behaviour (agent’s with defined behaviour follow the work proposed in [26]) for concern for self and concern for others dimensions. So, the $D_{Satisfaction}$ is remeasured using formula 5.

$$D_{Satisfaction} = \frac{D_{Satisfaction} \times CS + OAAD_{Satisfaction} \times CO}{CS + CO} \tag{5}$$

Where:

- CS is the value of Concern for Self $[1, 2, 3]$;
- $OAAD_{Satisfaction}$ is the average satisfaction of all the remaining agents;
- CO is the value of Concern for Others $[1, 2, 3]$.

The consensus level is measured with the value of the alternative that gathered more supporters, at the time t, during iteration i, or round r.

To evaluate our model, three simulation environments have been considered (12 Agents and 5 Alternatives; 12 Agents and 10 Alternatives; 40 Agents and 10 Alternatives). In each simulation environment, three experiments have been performed and the average satisfaction and consensus levels were measured. Each experiment was performed 100 times, in 900 simulations. For each simulation environment the information used in the configurations will be the same for the three experiments so that the results can be compared. However, these configurations (such as the agent's defined behaviour and its preferences) have been randomly generated. In the first experiment, agents are given the ability to forecast tendencies. In this first experiment, the agents use the first part of the model proposed in Section 2. The main idea is to study the consensus capacity and the final average satisfaction level of agents that can forecast tendencies and if those agents are capable to accept and include different alternatives in their objectives (which are not initially preferred) but still defend their initial preferences throughout the entire decision-making process (whenever those agents try sending new requests to persuade other agents). In the second experiment, agents use the complete model proposed in Section 2. This way, agents can forecast tendencies and change their preference towards which alternative should be used in the request (by using both parts of the model). As mentioned before, agents can change the alternative to use in each request if they identify that it is very unlikely to achieve a consensus for a certain alternative (which could also be their initial preferred alternative). This means they can change their objectives to achieve a better final satisfaction level compared to the one they would achieve if they allowed the alternative that they identified as a tendency to be chosen to solve the problem. In the third experiment, agents use the argumentation model without the concept that is proposed in this work. This means that the agents cannot forecast tendencies, but on the other hand will also never change their objectives which means they will never try to persuade other agents to accept alternatives different from what has been initially preferred by the decision-maker they represent. These agents are capable to advise the decision-maker about which alternative they should accept to maximize their satisfaction level. Both Figure 1 and Figure 2 are related to the first simulation environment. In this environment, we ran 100 simulations for each of three experiments described above. In Figure 1 it is presented all the consensus results obtained throughout 100 simulations for each one of these experiments. The consensus level achieved in the experiments of "Tendency Forecast + Request" and "Without Tendency Forecast" are very high (good). On the other hand, the consensus level obtained by the experiment of "Tendency Forecast" is quite low. The average consensus values for the experiments "Tendency Forecast", "Tendency Forecast + Request" and "Without Tendency Forecast" are 0.36, 0.67 and 0.64, respectively. In our opinion, the experiment of "Tendency Forecast" has the lowest average consensus level because even though agents are capable to identify tendencies and accept new alternatives that they consider to be advantageous, they still only send requests for alternatives initially preferred by the decision-maker. In practice, agents with just "Tendency Forecast" will not make true use of their ability to analyse tendencies. Agents have social skills and if they do not report nor show or make use of their change of opinion that will reflect negatively on the achieved results. Besides this, both agents with "Tendency Forecast" and "Tendency Forecast + Request" choose the alternative that they used in the last request (before the decision-making process ended) which will lead to agents with "Tendency Forecast" never using their social skills. This situation was always verified in the three simulations environments (see Figure 1, Figure 3 and Figure 5), and because of that the results analysed were mainly focused in the experiments "Tendency Forecast + Request" and "Without Tendency Forecast". In these 2 experiments, it was achieved very close average consensus level, in fact, in 62% of the times the same exact consensus level was achieved. In 25% of the times, agents with "Tendency Forecast + Request" achieved a higher consensus level and in the remaining 13% of the times, agents "Without Tendency Forecast" achieved a higher consensus level.

Figure 2 shows agents' average satisfaction results obtained throughout 100 simulations. The average satisfaction level obtained in the three experiments is very similar. Experiments with the same satisfaction level are differentiated by the consensus level that is achieved. It is important to note that the satisfaction is measured according to the alternative that the agent considered as his final choice at a time (t) and the alternative that at the same (t) gathered the highest consensus from all the agents. Another important point is that, in practice, the group satisfaction always tends to value 0. This happens mainly because only one iteration or one round is being simulated and no user reconfigurations will be made based on the information reported to the decision-maker. Therefore, this satisfaction evaluation is always related to the very first problem configuration. The average satisfaction level in the first simulation environment for "Tendency Forecast", "Tendency Forecast + Request" and "Without Tendency Forecast" are 0.09, 0.17 and 0.09, respectively. In this case, we can consider that there is a slight advantage for agents that

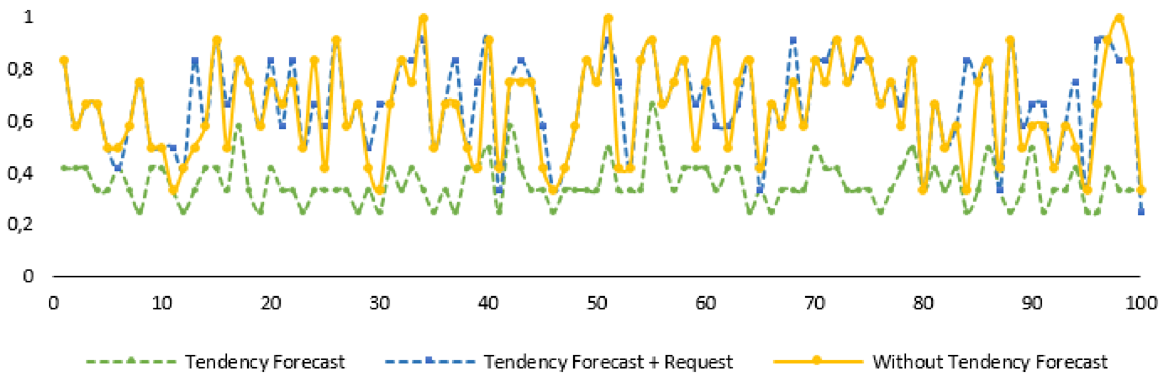

Figure 1: First Simulation Environment - Consensus

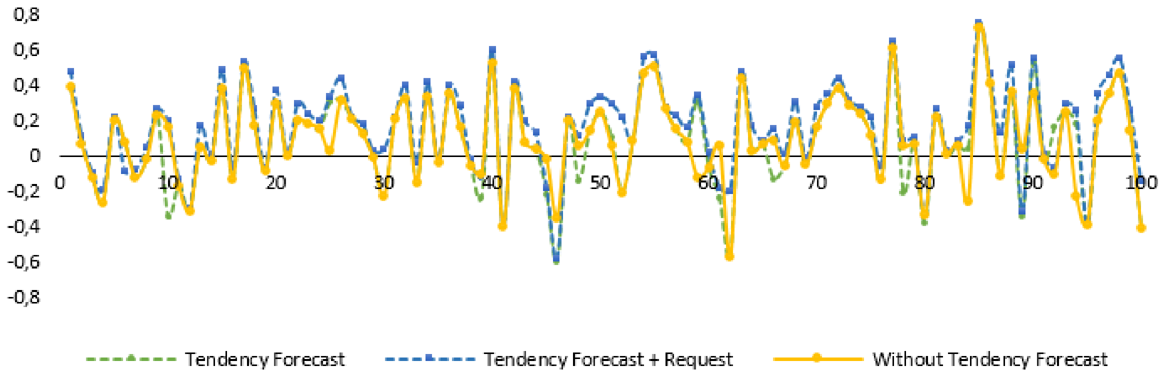

Figure 2: First Simulation Environment - Satisfaction

use "Tendency Forecast + Request".

One interesting fact is that agents with "Tendency Forecast + Request" and agents "Without Tendency Forecast", in 90% of the times, have achieved a consensus towards the same alternative which can tell us that the model here presented may not be too relevant in terms of finding the "best" solution. However, agents with "Tendency Forecast + Request" obtained a higher satisfaction compared with agents "Without Tendency Forecast" in 96% of the times. This means that agents usually achieved a consensus towards the same alternative (besides sharing the same argumentation model) due to the fact that we are considering a problem with a very low complexity level (12 agents and 5 possible alternatives).

Both Figure 3 and Figure 4 are related to the second simulation environment, where 12 agents aim to choose an alternative from a set of 10 possible alternatives. Similarly to the first simulation, the same three experiments will be analysed: when agents only use the first part of the model proposed in Section 2 (“Tendency Forecast”), or when agents use the complete model (“Tendency Forecast + Request”) or when agents do not use the proposed model (“Without Tendency Forecast”). Compared to the previous simulation environment it is clear that the complexity of the problem is much greater.

The consensus level achieved by the experiments of "Tendency Forecast + Request" and "Without Tendency Forecast" is still very positive. Similar to the first simulation environment the consensus level obtained by the experiment of "Tendency Forecast" is quite low. The average values of consensus for the experiments "Tendency Forecast", "Tendency Forecast + Request" and "Without Tendency Forecast" are 0.26, 0.57, and 0.51 respectively. This means that compared to the first simulation environment

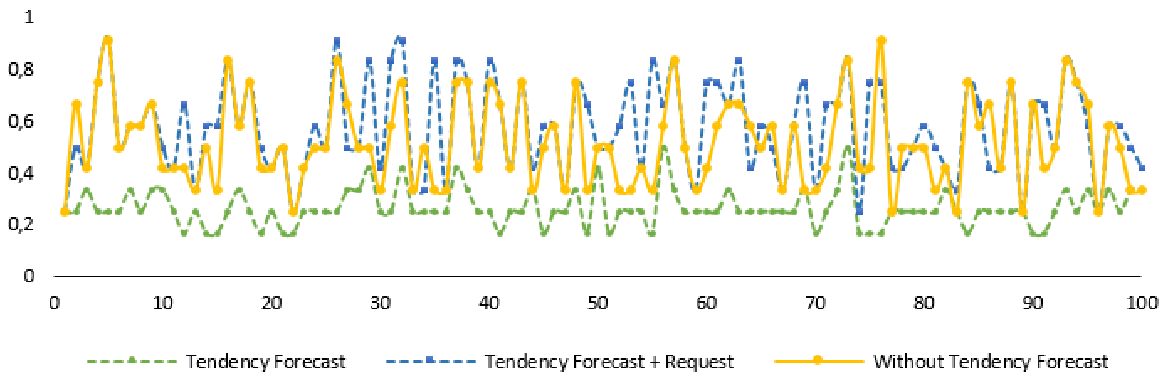

Figure 3: Second Simulation Environment - Consensus

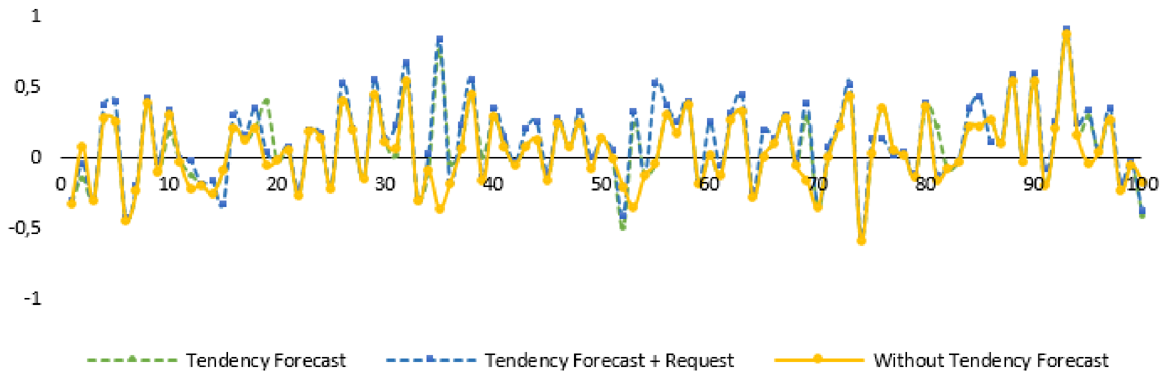

Figure 4: Second Simulation Environment - Satisfaction

there was a loss of 0.1, 0.1 and 0.13 respectively. This allows us to assume that not only do agents that use "Tendency Forecast + Request" achieve better results for satisfaction and consensus level; they also have the ability to deal with more complex problems better than agents "Without Tendency Forecast". Anyway, now, this is something that needs more evidence to be proved and that is the reason why the third and last simulation environment was considered, where 40 Agents e 10 Alternatives will be used so that the problem complexity can be even greater.

In this second simulation environment, agents with "Tendency Forecast + Request" obtained the same consensus level of agents "Without Tendency Forecast" in 53% of the times (less 9% compared to the first simulation environment). More importantly in this simulation environment (more complex) agents with "Tendency Forecast + Request" achieved a higher consensus level 37% of the times against only 10% of the times where agents "Without Tendency Forecast" achieve a higher consensus level.

Figure 4 shows the results obtained for the agents' average satisfaction level in the second simulation environment. Once again, the average satisfaction level obtained is very similar in both three experiments. The average satisfaction levels for "Tendency Forecast", "Tendency Forecast + Request" and "Without Tendency Forecast" are now 0.07, 0.12 e 0.04 respectively. There is still a slight remarkable advantage for agents that use "Tendency Forecast + Request". A very interesting fact compared with the first simulation environment is that now agents only achieved a consensus towards the same alternative 82% of the times. Knowing that agents that use "Tendency Forecast + Request" achieved the highest average satisfaction level, this may mean that when we are considering more complex problems agents with

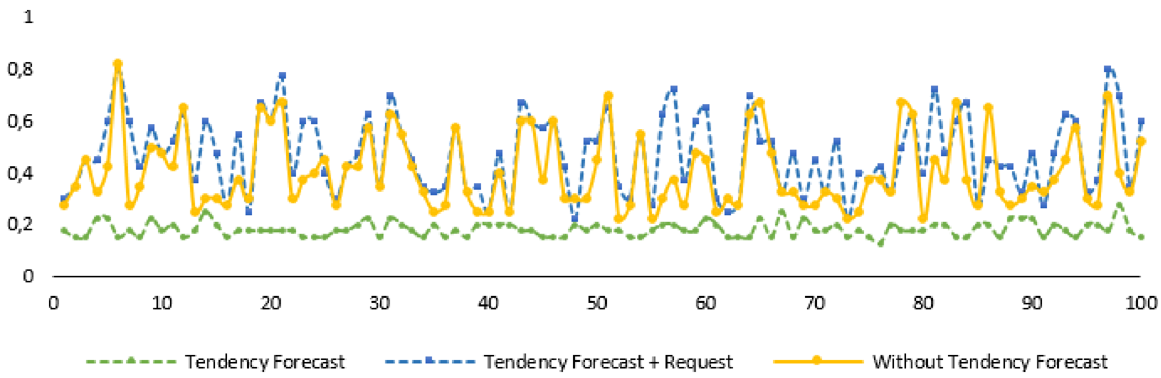

Figure 5: Third Simulation Environment - Consensus

"Tendency Forecast + Request" will achieve better decisions. It is also important to note that in 92% agents with "Tendency Forecast + Request" achieved a higher average satisfaction level against 7% of the times where agents "Without Tendency Forecast" achieved a better average satisfaction level and only in 1% of the times the same average satisfaction level was achieved in both situations.

Both Figure 5 and Figure 6 are related to the last simulation environment, where 40 agents attempt to achieve a consensus for an alternative from a set of 10 possible alternatives, and therefore will be the most complex scenario from the three studied in this work. In this scenario, it is also considered the three different experiments: when agents only use the first part of the model proposed in Section 2 ("Tedency Forecast"), or when agents use the complete model ("Tendency Forecast + Request") or when agents do not use the proposed model ("Without Tendency Forecast").

The consensus level achieved for the experiments of "Tendency Forecast + Request" and "Without Tendency Forecast" is 0.18, 0.47, and 0.40 respectively (Figure 5). This means that compared to the first simulation environment there was a loss of 0.18, 0.20 and 0.24 respectively. This allows us to assume that agents that use "Tendency Forecast + Request" obtain better results for the consensus level in either less or more complex problems.

In this last simulation environment, agents with "Tendency Forecast + Request" obtained the same consensus level as agents "Without Tendency Forecast" in only 23% of the times (less 39% compared to the first simulation environment). More importantly, it is in this simulation environment (the more complex) that agents with "Tendency Forecast + Request" have achieved a greater consensus level in 65% of the times against only 12% of the times where agents "Without Tendency Forecast" have achieved a higher consensus level. This shows that as the problem becomes more complex agents with "Tendency Forecast + Request" will also become better at achieving higher consensus levels and at more times compared with other agents.

Figure 6 shows the results for the average satisfaction levels obtained in the last simulation environment. Once again, the average satisfaction level obtained in three experiments is very similar. The average satisfaction levels obtained for "Tendency Forecast", "Tendency Forecast + Request" and "Without Tendency Forecast" are now -0.06, -0.02 and -0.09 respectively. This allows us to understand that agents that use "Tendency Forecast + Request" will always have the higher satisfaction levels, even if the problem is more or less complex. Once again, it was possible to identify a drop in the percentage where agents with "Tendency Forecast + Request" and agents "Without Tendency Forecast" achieve a consensus for the same decision, only happening 79% of the times. In 93% of the times, agents with "Tendency Forecast + Request" achieved a higher satisfaction level compared with agents "Without Tendency Forecast".

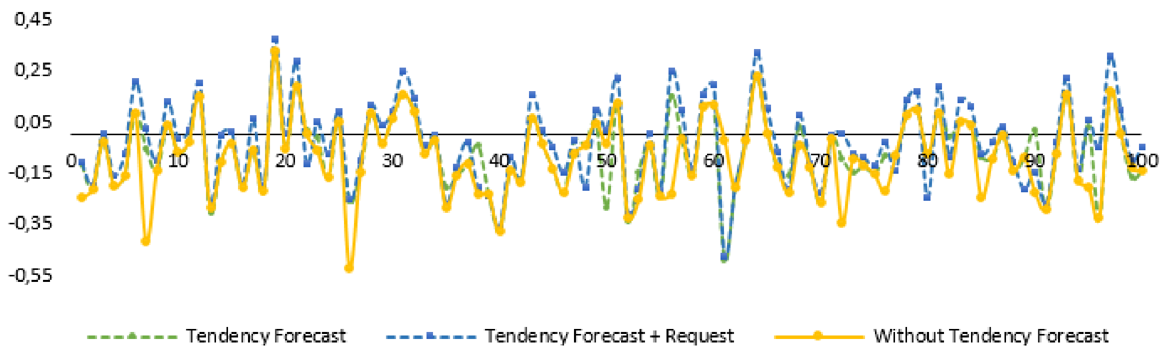

Figure 6: Third Simulation Environment - Satisfaction

4 Conclusions and Future Work

To support the decision-making process anywhere and at any time, Group Decision Support Systems have evolved to what we nowadays call as Ubiquitous Group Decision Support Systems. However, there are many existing problems associated to this type of systems. A system that has the main purpose of interacting with humans must show certain characteristics, such as: include the decision-maker in the process, make the process perceptible to the decision-maker, make interactions easier, allow the introduction of new information, data manipulation, suggest solutions with explanations, etc. Besides this, the type of negotiation practiced by decision-makers that work in the same organization also has distinctive characteristics. In this context, even though decision-makers are competitive while trying to convince others to accept their preferences, they also must be collaborative because it is important to achieve the best possible solution for the organization. This differentiates how negotiation models should be used and adapted to this kind of context from old approaches which we can find in literature, such as the seller-buyer example.

In this work, we propose a tendency analysis model with the goal to make GDSS that use negotiation models more intelligent. Our model has the main goal to improve the quality of the decision that is made as well as the group capacity to achieve a consensus. For that, agents that represent decision-makers must analyse the alternatives tendency and use the proposed algorithm to identify situations where they should reformulate their objectives.

To test our model and algorithm a case of study was performed with three different simulation environments that represent three different complexity levels. We could conclude that agents that use the tendency analysis model manage to achieve in average higher consensus levels when compared to agents that under the same circumstances do not use it. Besides this, agents that use the proposed model also manage to achieve higher satisfaction levels. We also concluded that has the context's complexity level increases, the tendency model becomes even more important. In the most complex simulation environment that we tested, agents with the ability to analyse tendencies achieved a higher consensus 65% of the times while agents that did not use this model could only achieve a higher consensus in 12% of the times. When measuring the satisfaction level in the same environment agents with the ability to analyse tendencies achieved a higher satisfaction level in 93% of the times. By combining both measures in the same study (satisfaction and consensus), it clearly shows the importance of providing agents with the ability to analyse tendencies to obtain decisions with higher quality in the context of this work.

As future work, we intend to expand our model. More precisely, we want to include in our model the analysis of credibility. Credibility (in a very simple way) can be important in situations when a decision-maker considers another to be credible. It might make sense to support his opinion despite the decision-maker's initial preferences. This way we think to be possible (together with automatic negotiation mechanisms) to achieve solutions with more quality as well as with higher consensus levels. The system will keep informing the decision-maker properly about each step of the negotiation process and the reasons behind suggestions that are given to him.

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